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Short Communication

Gait probability image: An information-theoretic model of gait representation

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ABSTRACT

In this paper, we propose a new probabilistic gait representation to characterize human walking for recognition by gait. The approach obtains the binomial distribution of every pixel in a gait cycle. Organizing the binomial distribution of all pixels in the gait image, we obtain the gait signature, which we denote as the Gait Probability Image (GPI). In the recognition stage, symmetric Kullback–Leibler divergence is used to measure the information theoretical distance between gait signatures. The experimental results reveal that GPI achieves promising recognition rates. Besides that, experiments on different walking speeds demonstrate that GPI is robust to slight variation in walking speed.

1. Introduction

Most of the computer vision-based human recognition methods, such as iris, fingerprints, face, or palmprint biometric modalities, generally require a cooperative subject, specific views, physical contact or close proximity. Gait, which concerns recognizing individuals by the way they walk, is an alternative biometric without these requirements. However, gait also has some limitations. Gait can be affected by clothing, shoes, physical and emotional conditions or environmental context. The gait variation of the same person under different conditions reduces the discriminating power of gait as a biometric, but the inherent gait characteristics of an individual still makes it irreplaceable in visual surveillance applications [1].

Previous work on gait recognition can be mostly divided into two categories: model-based approaches and motion-based approaches. Model-based approaches [2–7] explicitly model the structure of the human body. These approaches usually measure parameters on the model such as trajectories, limb lengths, and angular speeds. Though model-based approaches are view and scale invariant and reflect the kinematic characteristics of walking manner, they are hard to accurately locate the joint positions due to the highly flexible structures of non-rigid human body and to self-occlusion [8,9]. Therefore, later literature focuses more on motion-based approaches.

Motion-based approaches [10–17], on the other hand, characterize gait motion pattern, without regard to its underlying structure. Among the motion-based approaches, there is an effective method which engages gait energy image (GEI) [1,18] as gait signature. The GEI is a time-normalized accumulative energy image of human walking in a complete gait cycle. Yang et al. [19] used variation analysis to construct a dynamics weight mask to enhance the dynamic region in GEI and to suppress the noises on the unimportant regions. Chen et al. [20] constructed the frame difference energy image (FDEI) of a frame by adding the dominant energy image (DEI) of the corresponding cluster in a gait cycle and the positive portion of the frame difference between consecutive frames. Zhang et al. [21] proposed an active energy image (AEI) method by accumulating image difference between subsequent silhouette images. Lam et al. [22] generated a gait flow image (GFI) using the optical flow field from the gait image sequence. Bobick and Davis [23] explored two temporal templates: motion energy image (MEI) to indicate the presence of motion in a gait cycle, and a motion history image (MHI) as a function of the recency of motion in a gait cycle. Wang et al. [24,25] preserved the temporal information in a gait cycle via color mapping to generate a chrono-gait image (CGI). These approaches however represent a complete gait cycle as a single composite image, limiting the transient information captured.

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Walking humans are self-occluding and non-rigid articulated objects. As a result, we might have great difficulty extracting gait features accurately. However, if we examine a spatiotemporal XYT volume of a set of walking people, some distinctive patterns reveal themselves, suggesting that spatiotemporal analysis may be useful. Many approaches characterize motion via spatiotemporal XYT data volume spanned by the moving person in the image. Niyogi and Adelson [26] delineated deformable contour patterns by taking spatiotemporal XYT slices of the image volume. Liu et al. [27] used Frieze patterns to represent gait along the time axis. Yu et al. [28] applied three dimensional Fourier transform to the gait volume to obtain a unique frequency for each person's walking pattern. Huang and Wang [29] extracted energy images by projecting the XYT volumes onto X–T plane. Kellokumpu et al. [30] described gait using spatiotemporal histograms of Local Binary Patterns from Three Orthogonal Planes (LBP-TOP). Ang et al. [31] applied a wavelet maximum average correlation height (MACH) filter on spatiotemporal volume in activity recognition.

In this work, we propose a spatiotemporal probabilistic gait representation. Unlike most state-of-the-art methods that compute the spatial patterns of individual image separately and then accumulating them as a time sequence, we present a novel method to describe the statistics of motion patterns over time.

The fundamental assumptions made here are: *The pixel at each coordinate point in a gait cycle is defined as an independent Bernoulli trial, which has only two possible outcomes: foreground and background.* We treat every pixel in the gait image as a Bernoulli random variable. Considering all the frames in the gait cycle, we compute the binomial distribution of each pixel. Thereafter, the mean and the variance of the distribution is obtained. Accumulating the mean and variance of all pixels in the image, we construct the gait signature, which we denote as the Gait Probability Image (GPI). In the experiments, we use symmetric Kullback–Leibler (KL) divergence to measure the information theoretical distance between the gallery and probe probability distributions. Unlike other gait representations which consider gait as a sequence of templates, our approach represents human motion using probabilistic statistics.

2. Gait signature extraction

This section outlines the procedures of the proposed approach.

2.1. Gait period estimation

We assume that silhouettes have been extracted from original human walking sequences. A silhouette preprocessing procedure [32] is then applied on the extracted silhouette sequences. Firstly, size normalization is performed where each silhouette image is proportionally resized so that all silhouettes have the same height. Then, horizontal alignment is performed where the silhouettes are centered with respect to its horizontal centroid.

Human walking is a periodic activity with each gait cycle covering two strides — the left foot forward and right foot forward strides. Each stride spans the double-support stance to the legs-together stance and back to the double-support stance. We estimate the gait period based on the time signal series of silhouette width of each frame. The frame associated to a local maximum (of silhouette width) corresponds to the double-support stance, which we denote as the key frame. On the other hand, the frame associated to a local minimum corresponds to the legs-together stance.

Each video is divided into a number of gait cycles, where each cycle is bounded by alternate key frames. Fig. 1 illustrates the time signal series of silhouette width and the corresponding gait image at local maximum (key frames) and local minimum frames.

2.2. Gait probability image

Consider a gait cycle with n preprocessed binary image frames where every pixel in the cycle is an independent Bernoulli trial. We treat pixel intensity $X_{ij} \in \{0,1\}$ at every coordinate point (i,j) as a Bernoulli random variable, where value 0 denotes background and value 1 denotes foreground with motion.

The probability of the pixel at coordinate point (i,j) being foreground in an image is given by

$$P(X_{ij} = 1) = p_{ij} \tag{1}$$

and the probability of the pixel at coordinate point (i,j) being background is

$$P(X_{ij} = 0) = 1 - p_{ij}. \tag{2}$$

The binomial distribution of the random variable X_{ij} is fully characterized by the parameters n and p_{ij}, i.e.,

$$X_{ij} \sim B(n, p_{ij}).$$

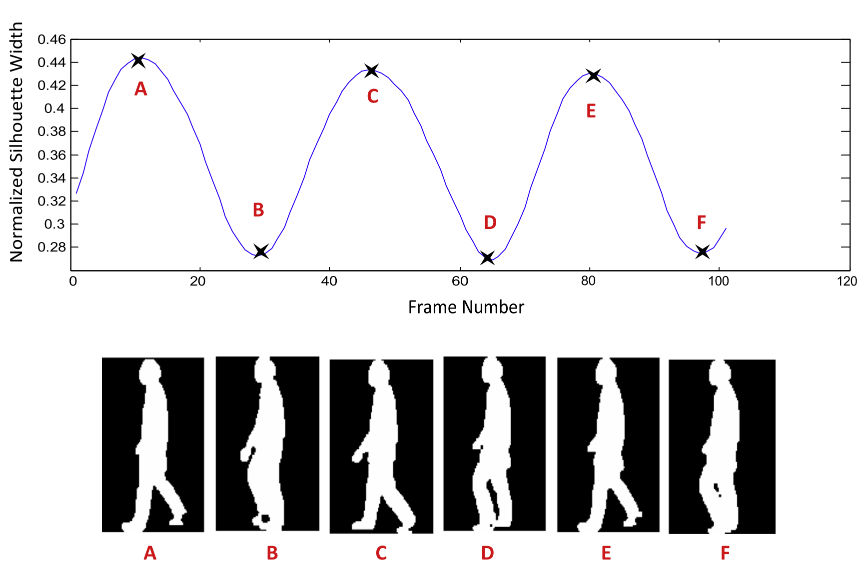

Fig. 1. Top row shows the time signal series of silhouette width. Bottom row shows the corresponding gait image at local maximum and local minimum frames.